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Original Article

Automation of Sunspot Detection and Image Transmission by Machine Vision Processing at the Observatory of the Geophysical Institute of Peru, Province of Chupaca: Design and systemic modeling

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Abstract - *This paper presents the design and implementation of an autonomous sunspot detection and transmission system developed at the observatory of the Geophysical Institute of Peru, in the province of Chupaca. Given the need for real-time solar monitoring systems at national observatories, the first stage involved developing an artificial vision model based on YOLOv7 together with the ODROID H4 Ultra processor. This computational model provides 70% efficiency compared to manual systems, calculated using performance metrics. In the second stage, the solar telescope was equipped with updated solar filters to enhance image recording. The overall operational performance of the system was largely positive, due to the accuracy of detection and ease of data transfer provided by the current processors. Validations between national or international observatories are recommended. Finally, the continuous improvement of the system developed for astronomical and research purposes is considered promising.*

Keywords - *Astronomical Observatory, Automation, Machine Vision, Real-Time Monitoring, Sunspot Detection.*

1. Introduction

Solar observation has gained considerable momentum in recent years, mainly due to technological advances. Along these lines, the European Space Agency (ESA) and NASA's 2019 Solar Orbiter space mission provided high-resolution photographs of sunspots, allowing us to learn about previously unknown aspects [1]. Recently, significant advances have been reported in understanding the magnetic structure of sunspots [2]. In addition to terrestrial records using telescopes, artificial vision detection has also been used [3, 4].

However, some observatories are still known to use rudimentary manual methods to record the dynamic behavior of sunspots, which are repetitive and limited [5-7]. Such is the case of the heliograph telescope, located in the area known as SECASI at the Geophysical Institute of Peru (IGP), which uses the "attenuated direct vision" system, which consists of projecting the image of the sun onto a paper surface from a telescope, making sunspots visible and allowing the corresponding tracings to be made [8]. Sunspots are known to influence Earth's climate, as well as telecommunications and electrical grids [1, 9], underscoring the importance of monitoring this phenomenon. Traditionally, this has been based on manual procedures, which are increasingly limited by the growing volume of solar data. In this context, automation through image-based grouping and counting offers a compelling alternative [10].

Despite advances in automated sunspot detection using computer vision techniques, most existing studies remain limited to offline analysis or controlled environments, with scarce validation in real-time operational observatories that still rely on manual recording procedures [3, 10].

This gap underscores the need for automated, integrated, and operationally validated systems for continuous sunspot monitoring. In response to the identified research gap, this article presents an integrated real-time automated system for sunspot detection using computer vision techniques, validated under operational conditions at the IGP observatory.

Unlike existing studies limited to offline or laboratory-based analysis, the proposed system improves image visualization and processing while enabling automated monitoring and transmission within a real observatory environment [11, 12].

2. Literature review

2.1. Context of Sunspot Detection

Sunspots are areas on the sun's surface that are cooler than the surrounding area (about 1000–1500 K cooler). This is because intense magnetic fields prevent heat from rising to the surface as plasma [4]. From Earth, we can observe these areas of thermal difference as dark spots [20, 21]. In relation to the above, García et al. mention that sunspots are directly related to solar activity, therefore significantly influencing the space surrounding the Earth.

According to Hayakawa et al., one negative aspect is the high degree of variation in the results obtained by experienced observers in manual detection and classification activities [8]. From this perspective, Hanaoka states in his study that this condition reduces the reliability of historical records [3].

The detection and recognition of sunspots is often mistakenly considered a simple task. On the contrary, G. Gkioxari et al., in their study "Mask R-CNN," state that the accuracy of the results contains a high degree of subjectivity in terms of their interpretation [24]. In this regard, they propose a pixel segmentation methodology—studies such as T.-Y. Lin et al., "Microsoft COCO," propose that the data set be standardized and reproducible, with the aim of reducing the level of observational uncertainty [22].

2.2. Development of Detection Methodologies

Sánchez-Levega indicates that classical techniques are mainly based on digital image processing, including luminarization, edge detection, region growth, and mathematical morphology. This development allowed for the efficient detection of dark regions in high-contrast images. The aforementioned methodologies depend on manual configurations that are vulnerable to unintentional biases [6]. In agreement, Hanaoka supports the idea that low-quality images processed using these methodologies present omissions of sunspots as well as false positives [3].

S. Carvalho et al. mention that the Observatório Geofísico e Astronómico da Universidade de Coimbra (Portugal) developed automatic methods that implement geometric feature extraction tools combined with more accurate statistics [4]. In relation to this, Lourenço et al. mention that this development allowed for the analysis of longer solar cycles [11].

However, S. Carvalho et al. point out that systems such as those used at the observatory in Portugal can be affected by noise. Another problem is that the results obtained when processing low-contrast solar images can vary greatly [4].

2.3. Automated Systems for Sunspot Identification

There is a growing interest among observers in developing new automated sunspot detection systems. Carvalho et al., in their study "Comparison of automatic methods to detect sunspots in the Coimbra Observatory spectroheliograms," introduce automated processing techniques using logical operators in order to minimize human intervention. The results show that this developed methodology offers greater stability compared to traditional and semi-automatic methodologies [4]. Hanaoka, for example, expresses his preference for automated methods over traditional ones. He also highlights the potential and level of confidence provided by logical operators applied to data collection [3].

In a recent study, Zhao et al. designed a methodology for sunspot classification and number counting using automated SDO/HMI imagery. This study demonstrates improved consistency in sunspot detection [10]. In this context, the authors point out that the segmentation of faint sunspots, coupled with inclement weather that hinders observation, remains a challenge. Other challenging conditions include noisy images and images with lighting defects [8, 10].

2.4. Deep Learning-based Approaches

The rapid evolution of deep learning has brought about a revolutionary change in the automatic detection of sunspots. Mkwanda et al. described a method based on convolutional architectures with bidirectional analysis for classifying and detecting sunspot clusters, showing remarkable improvements over manual methods in both accuracy and generalization [2]. These findings revealed the advantage of extracting spatial representations directly from the data, eliminating the dependence on manually designed features.

Mourato et al. and Sayez et al. extended this approach by adding semantic and instantiated segmentation techniques, which improved the identification of sunspot clusters and individual sunspots, as well as allowing for a more detailed study of their internal structure [16, 17]. While these methods provide more comprehensive information than simple detection of active regions, the authors caution that their high computational load makes them challenging to implement in real-time systems.

For the reasons outlined above, several studies demonstrate that models based on deep segmentation reduce bias and exhibit greater generalizability. However, Mourato et al. and Sayez et al. [17], In their study, they emphasize that a critical factor remains the computational efficiency of these methodologies when integrated into embedded platforms for real-time processing.

2.5 Real-Time Detection and Efficient Architectures

In recent times, interest in studying the behaviour of spatial objects has been increasing; therefore, there is an ongoing effort to find effective ways of analysing and monitoring such behaviour. Of these methods, computer vision models have emerged as one of the best, due to their ability to fulfil the task with both accuracy and speed. Baek et al. Optimised a deep learning method for object detection through architecture changes [19]. Based on this context, it is no surprise that the YOLO algorithm has gained popularity over time.

The YOLO algorithm has made substantial progress, with the release of YOLOv7 now allowing for the realisation of an optimal combination of performance and speed of object detection. Wang et al. found that YOLOv7 has outperformed earlier versions of YOLO as well as other feature detectors, thus making it a very tough competitor when it comes to computer vision and real-time detection [13, 21].

One of the ongoing challenges of implementing computer vision models is the limitation of computational power as well as energy consumption. To address these needs for computer vision applications, the use of compact, high-performance devices is necessary; one such device is the ODROID H4 Ultra, which is a single-board computer that allows for the running and monitoring of an object detection model in real time whilst still maintaining a reasonable level of performance [13, 19].

2.6. Comparative Synthesis and Research Gaps

A review of the literature reveals a clear transition from classical methods, through semi-automatic methods, to fully automated systems based on Deep Learning. The first methods defined how to detect sunspots, as well as defining some characteristics that would later be useful for more modern methods. However, the classical methods were minimal and wildly inaccurate. On the other hand, current methods based on Convolutional Neural Networks (CNN) have achieved significant improvements in segmentation and classification, but they require greater computational power [2, 4].

Although there are still some gaps in optimally integrating accurate detection, real-time tracking, and processing, many studies prioritize model accuracy without verifying whether its integration is feasible within the devices being used. This often limits the actual application of models for continuous monitoring [14, 17].

2.7. Proposed Framework based on YOLOv7 and ODROID h4 Ultra

As mentioned in the literature, there are many limitations when implementing a computer vision system with real-time monitoring due to high computational requirements. Therefore, it is necessary to adopt a framework that combines accurate automatic detection, high inference speed, and compatibility with embedded systems. Considering these characteristics, Wang et al. demonstrated that YOLOv7 outperforms other methods, meeting the previously established requirements and being suitable for real-time monitoring applications with low computational demands [13]. The ODROID H4 Ultra allows for the application of the system accuracy, scalability, and real-time processing offered by YOLOv7. This proposal is a reliable and highly replicable solution for automatic monitoring projects of sunspots or space objects that goes hand in hand with current lines of research in solar observation and computer vision systems [2], [19]. Consequently, Table 1 shows the information in a compact form based on the literature reviewed in this study, taking into account the key points found in each approach.

Table 1. Comparison of sunspot detection approaches, their main limitations, and representative references

Phase	Main Approach	Key Limitations Identified	Representative References
Traditional observation	Visual inspection, manual classification	Subjectivity, observer, variability	[3, 20, 21]
Early automatic methods	Thresholding, morphology, region growing	Manual tuning, noise sensitivity	[3, 6, 11]
Automatic systems	Image-based and morphological pipelines	Low robustness under poor conditions	[4, 8, 10]
Deep learning approaches	CNN-based detection and segmentation	High computational cost	[2, 14, 15, 16, 17]
Real-time optimized models	One-stage detectors (YOLO family)	Embedded constraints	[13, 19, 21]
Proposed framework	YOLOv7 + ODROID H4 Ultra	Hardware-dependent performance	This work

3. Materials and Methods

3.1. Research Design

The research focuses on the design and modeling of a system that automatically detects sunspots and transmits them in real time. To achieve this, artificial vision techniques were used, as this technology improves efficiency and minimizes human intervention in the detection of sunspots, whose data can then be more easily collected by the Geophysical Institute of Peru (IGP). YOLOv7 was used to develop the prototype, as it is an accurate model with high real-time processing capacity without requiring high computational power, making it the best option for the project, which uses a medium-capacity microcontroller that will be used continuously for several hours [13].

3.2. Materials and Equipment

An SVBony SV105 camera with various optical attachments (0.5x focal reducer, IR/UV-ND3.0 0 filters, and a Baader filter) to capture images of the sun directly from a telescope. An ODROID H4 Ultra was used as the controller, which is a single-board computer with sufficient capacity to deploy the computer vision model.

A screen was added to these components so that the recorded data could be observed. In terms of software, the YOLOv7 detection algorithm was applied due to its remarkable ability to detect objects in real time. This was complemented by the OpenCV library for processing, TensorFlow Lite for inference, and MQTT/REST protocols for data transmission.

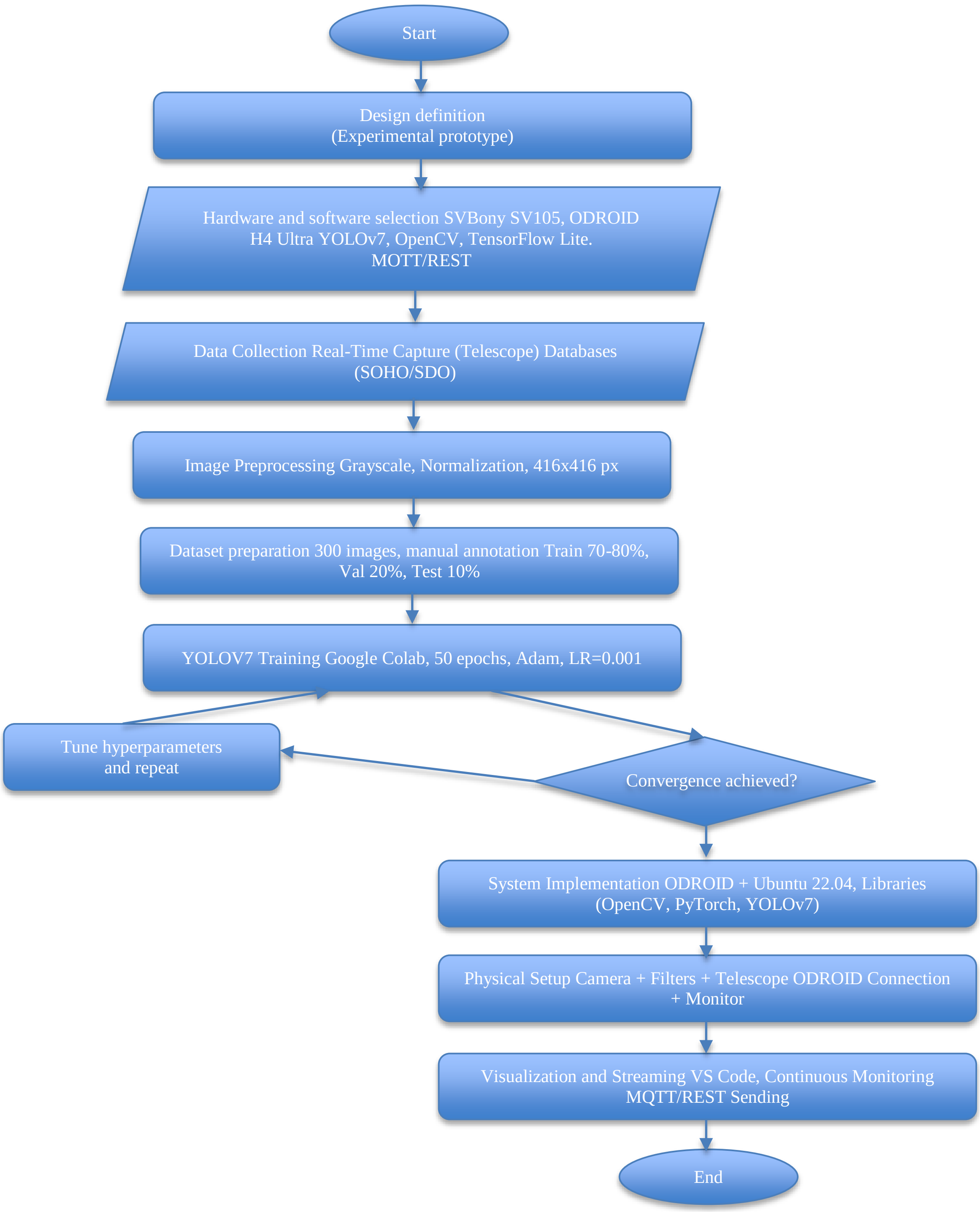

Fig. 1 Process flow representation of the experimental methodology followed for system development and validation

3.3. Procedure

3.3.1. Preparation of the Dataset

A total of 300 images of the sun were collected from public databases and telescope captures. The number of images was chosen because sunspot patterns are not highly complex and are unlikely to be confused with any other object, as they are superimposed on the sun. The processing capacity of the microcontroller was also taken into account, as it would not be able to handle a large number of images, given that a larger set would produce results similar to those obtained with the current size of the dataset. The sunspots were labeled manually using the labels "Sol" and "Mancha." High precision was maintained when selecting the areas of interest, labeling even the smallest ones in order to obtain better Training and enable the model to detect as many spots as possible. The dataset was exported in a format suitable for YOLO V7.

3.3.2. Training the Computer Vision Model

The dataset was divided into Training (80%), validation (20%), and testing subsets. YOLOv7 was trained in Google Colab, producing output images with sunspots highlighted and confidence scores assigned.

3.4. Implementation of Real-Time Visualization

The trained model was integrated for real-time object detection, using live camera input and multithreading for simultaneous detection and monitoring. The system was compiled into an executable file to ensure portability.

3.5. Installation of Physical Components

To assemble the prototype, the UV/IR filter, 0.5x focal reducer, and ND3.0 filter were first installed on the SVBony SV105 camera lens, which was then positioned on the telescope eyepiece using a steel coupler. Next, the Baader filter was placed on the telescope's primary lens.

Once everything was correctly positioned on the telescope, the camera was connected to the ODROID H4 Ultra, which was previously connected to the monitor.

3.6. Ground Truth and Annotation

Instituto Geofísico del Perú (IGP) provided a set of data, including manual records of sunspots taken at its headquarters in the city of Ica, as well as photographs of the sun provided by collaborating observatories. Standard tables used in sunspot recording were used as a reference for data selection, and existing catalogs were also used to compare the model.

Sunspots were classified according to their visual contrast, size, and shape consistency. After classifying all the images, the dataset was divided into 70% for Training, 20% for validation, and 10% for testing.

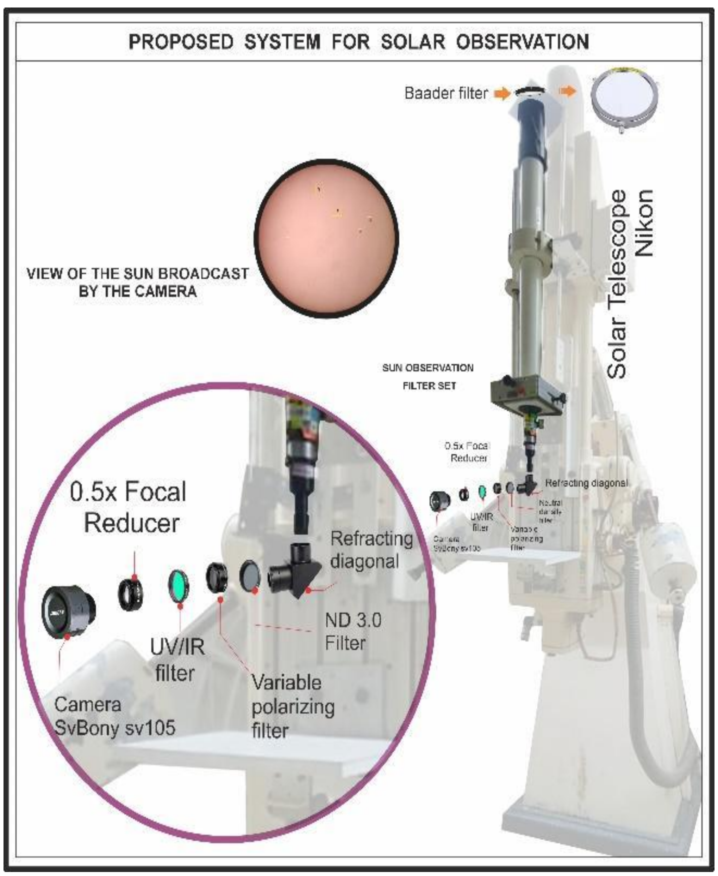

Fig. 2 Positioning mode for filters and the astronomical camera

4. Results and Discussion

A system was created to identify sunspots in the Visual Studio Code development environment, using computer vision methods. The effectiveness of the system was verified by analyzing photographs obtained with the SvBony S105 astronomical camera, which included polarizing filters, IR filters, UV filters, Baader filters, and cutoff filters. All data processing and analysis were carried out on the ODROID H4 Ultra platform.

4.1. Validation and Analysis of Results

Tests were carried out with different image groups to verify the system's accuracy and precision. Images that had already been classified were used for validation, and the results generated by the model were compared with established reference standards. The system showed an accuracy greater than 70% in identifying sunspots. It was noted that as more images were incorporated into the model training, the accuracy increased. Comparative analyses with manual or traditional detection systems showed that the implemented system reduces the time required for detection and significantly increases the consistency when identifying sunspots.

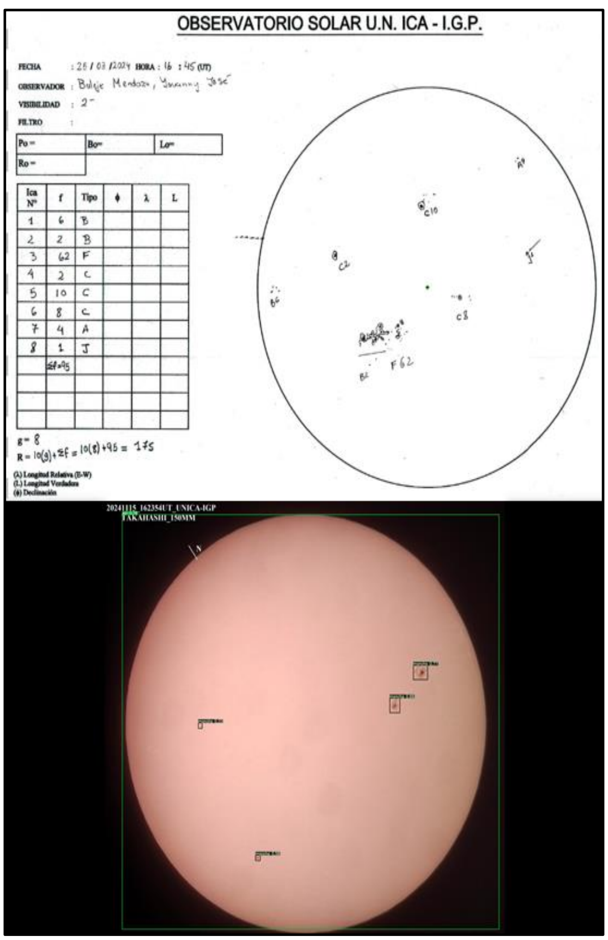

Fig. 3 Comparison of accuracy between manual detection methods and the automated system

4.2. Automation Stability and Efficiency

The stability and effectiveness of the system in solar monitoring were evaluated through continuous operation tests.

- Real-time Processing – The system produced a detection output (i.e., Predictions) every 900 ms with an average speed of 30 FPS. So, for all detected samples, the predicted image was processed with no delay.
- Operational Efficiency – The continuous flow of data from an analysis of images collected hourly by the system and processed continuously allowed for uninterrupted analysis and a consistent flow of information.
- Computational Efficiency – A combination of the effectiveness of the YOLOv7 model and the use of an ODROID H4 Ultra Processor proved to be cost-effective when performing these high-demand computations.

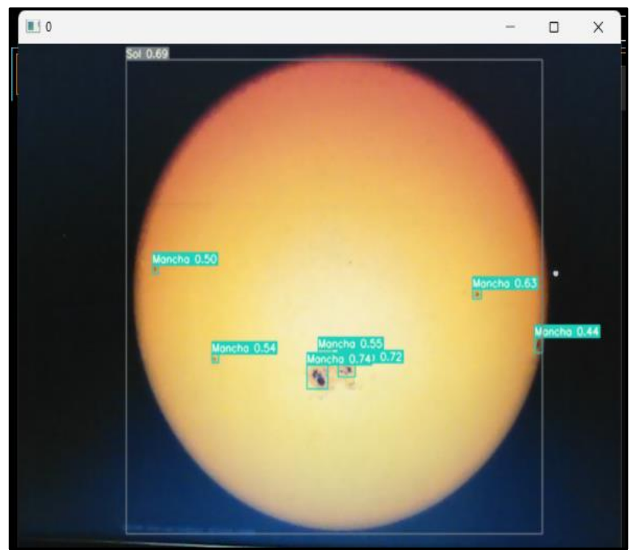

Fig. 4 System performance with image detection every 900 Ms or So

4.3. Analysis of Solar Detection Solar Patternss

The performance of detection, in addition to its accuracy and processing speed, was assessed using a Precision-Recall (PR) analysis, which is specifically designed to work with object detection problems where there exists class imbalance between the different classes of objects.

As seen from the PR Curves, the detection system had an overall strong performance with an mAP@0.5 score of 0.922, whereby the average precision of the "Sol" detection class was 0.994, while the detection class of the "Manchas" was only 0.850, which indicates that sunspot localization was much more complex than solar disk identification.

Thus, it is clear from these findings that the system has a high level of precision at high levels of recall, making the use of PR analysis as an evaluation metric more appropriate than using ROC analysis to evaluate this type of application, that is, detection-based.

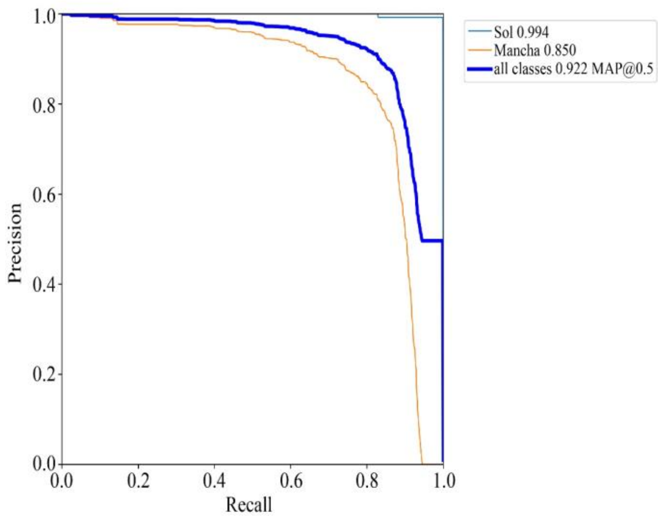

Fig. 5 Precision–Recall Curves of the Proposed Sunspot Detection System

4.4. Error Analysis

To analyze errors resulting from the validation process, confusion matrices and F1-score curve datasets were created. The majority of error sources fall between low-contrast imaging and small sunspot patterns, particularly in regard to those sourced from the Mancha classification. As indicated by the F1-score curve, most of the confusion between accurate positive and false negative detections is consistent across all levels of the continuum, indicating that confidence thresholds can be relied upon irrespective of how robust they are at any point on that continuum.

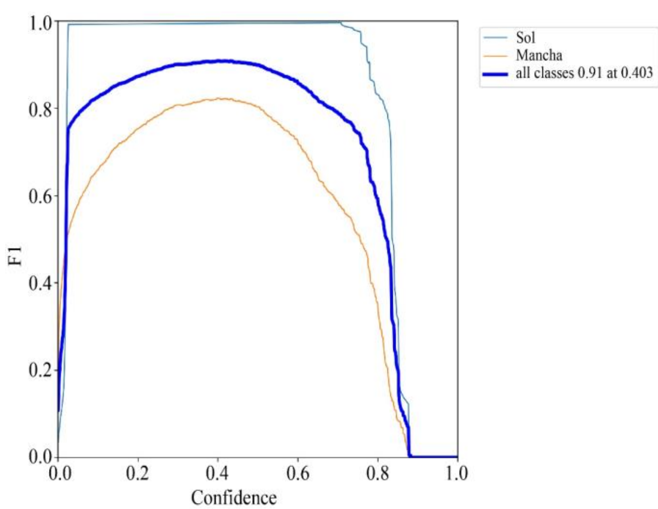

Fig. 6 F1-Score as a function of the confidence threshold for the proposed sunspot detection system

From the data in the confusion matrix, it was possible to discern that the majority of misclassifications between sunspot patterns occurred between the same visual types: those having small, low-contrast regions. Due to this visual similarity, there was less precision in detecting sunspots in the Mancha category.

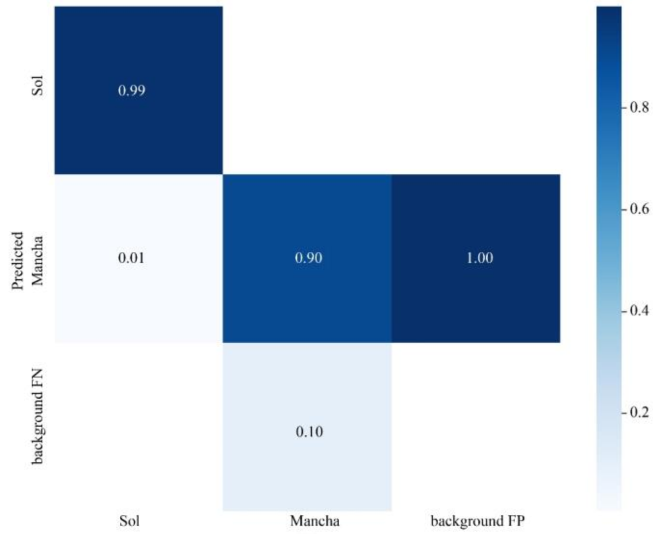

Fig. 7 Confusion Matrix Illustrating Classification Performance and Misclassification Patterns

4.5. Generalization

Generalization was evaluated on an independent set (10%) with unseen images, showing stable performance under varying illumination and filter conditions. Potential failures with minimal sunspots and bias from medium-resolution telescopes were acknowledged. External validation with images from other observatories is proposed to ensure robustness.

- The system has accurately identified important patterns in solar activity and provided additional research for future studies.
- Detection and tracking: The number of sunspot detections has been correlated with solar activity predictions from previous literature.
- New structures were found that were not previously identified when the process was performed manually.

The system proved its effectiveness in identifying the vast majority of sunspots in real time, with a processing speed of 30 frames per second, allowing for uninterrupted monitoring.

The combination of YOLOv7 and the ODROID H4 Ultra optimized image processing, enabling fast and efficient identification of critical solar patterns. This demonstrated that both systems represent a viable alternative to traditional methods used in smaller-scale observatories with limited budgets.

The manual approach is the standard in the work of Carvalho et al. in 2020. It is used to analyze automatic algorithms; however, it is not entirely perfect, as it has limitations inherent to manual work and is highly likely to overlook more minor stains or those that are less noticeable to humans.

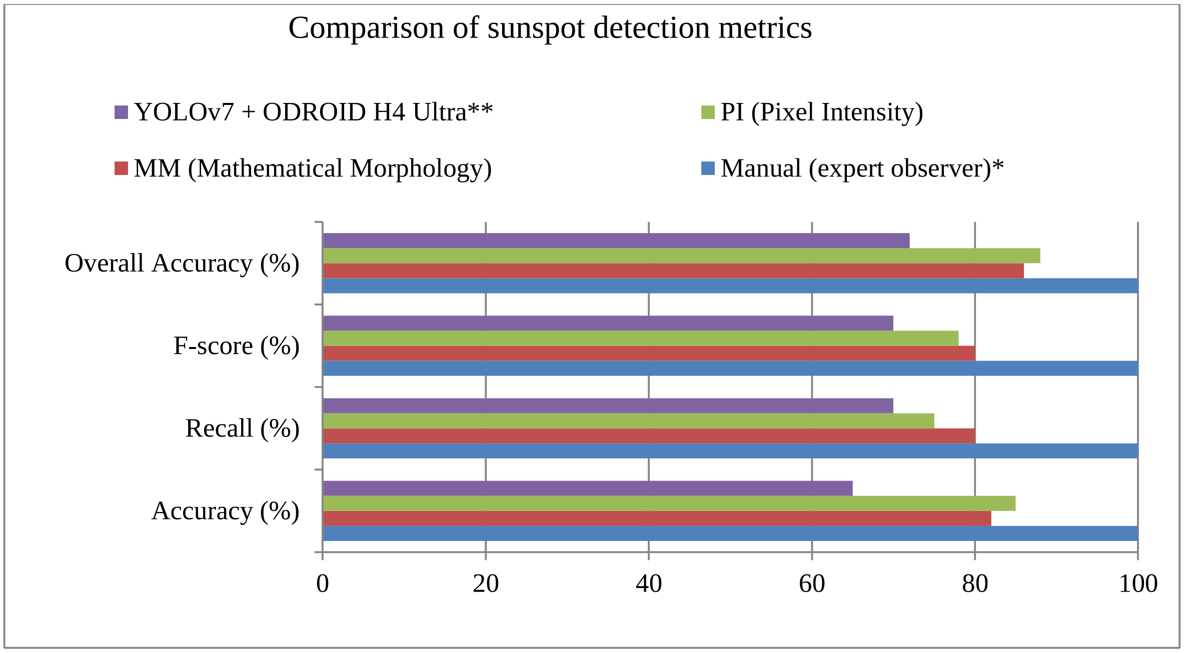

Fig. 8 Contrast between sunspot detection measures using the traditional method and methods using computer vision (MM, PI, and YOLOv7)

Table 2 summarizes the most important findings of the system, along with their assessment, emphasizing the key performance indicators and the most notable contributions of the analysis.

Table 2. Most relevant results of the automatic sunspot detection system

Area evaluated	Result obtained	Support
System accuracy	>70% in sunspot detection	Experimental validation (this study).
Processing speed	30 fps in real time	Implementation on ODROID H4 Ultra + YOLOv7 (this study).
Detection latency	~900 ms per event	Continuous operation testing (this study).
Operational stability	Sustained image processing every minute without interruptions	Long-term testing (this study).
Scientific contribution	Identification of solar patterns not visible in manual methods	Consistent with Hanaoka (2022).

Although Training with large volumes of data is often limited by the need for manual annotations, it has been shown that this process can be optimized and observer bias reduced through semi-supervised methods that generate automatic labels [14].

The YOLOv7 + ODROID H4 Ultra system exceeds 70% in preliminary performance metrics, with critical advantages in speed (real-time detection at 30 fps), reduction of human bias, and scalability for continuous monitoring, making it an up-and-coming alternative for observatories with limited resources.

The competitive performance of the proposed system can be attributed to the use of the YOLOv7 architecture, which enables efficient real-time detection, and its deployment on lightweight hardware suitable for continuous operation. Compared with previous approaches reported in the literature [14, 15], which are mainly evaluated on offline or satellite-based datasets, the proposed method was validated under real observational conditions, making it particularly suitable for ground-based observatories with limited resources.

5. Conclusion

At the end of the project, it was demonstrated that the system is an effective tool for automatic sunspot detection. By combining YOLOv7 with the ODROID H4 Ultra, a balance was achieved between the cost and performance of the system. The implementation of the project is valid for use in observatories with limited resources, where significant infrastructure changes are not possible, but adding a system with high technological capabilities will be of great help for research and data collection on sunspots.

Various filters located on the camera (UV/IR filter, ND3.0 filter, and Sybony Baader filter) were used to capture the solar image. The use and selection of appropriate solar filters play a crucial role in detecting sunspots, as well as in preserving the sensor of the astronomical camera. On the other hand, the implementation of an artificial vision system for observatories such as IGP in the field of monitoring could improve the efficiency of the recording, collection, and scientific dissemination tasks that these institutions provide to the community. Additionally, its low implementation cost makes it accessible for low institutional budgets without reducing image quality and efficient management of data obtained in real time.

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